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The climate and air quality benefits of wind and solar power in the United States

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Wind and solar energy reduce combustion-based electricity generation and provide air quality and greenhouse gas emission benefits. These benefits vary dramatically by region and over time. From 2007 – 2015, solar and wind power deployment increased rapidly while regulatory changes and fossil fuel price changes led to steep cuts in overall power-sector emissions. Here we evaluate how wind and solar climate and air quality benefits evolved during this time period. We find cumulative wind and solar air quality benefits of 29.7 – 112.8 billion US 2015$ mostly from 3,000 – 12,700 avoided premature mortalities, and cumulative climate benefits of 5.3 – 106.8 billion US 2015$. The ranges span results across a suite of air quality and health impact models and social cost of carbon estimates. We find that binding cap-and-trade pollutant markets may have reduced these cumulative benefits by up to 16%. In 2015, based on central estimates, combined marginal benefits equal 7.3 ¢/kWh (wind) and 4.0 ¢/kWh (solar).

Wind and solar energy provide air quality, public health, and greenhouse gas (GHG) emission benefits as they reduce the reliance on combustion-based electricity generation. In the United States these benefits vary dramatically by region and over time. In the last decade, wind and solar deployment has increased more rapidly than any other non-combustion based electricity generating technology; at the same time, regulatory changes and fossil fuel price changes have led to steep cuts in overall power-sector emissions of criteria air pollutants and CO_2. These changes prompt the question: have wind and solar energy benefits changed over time?

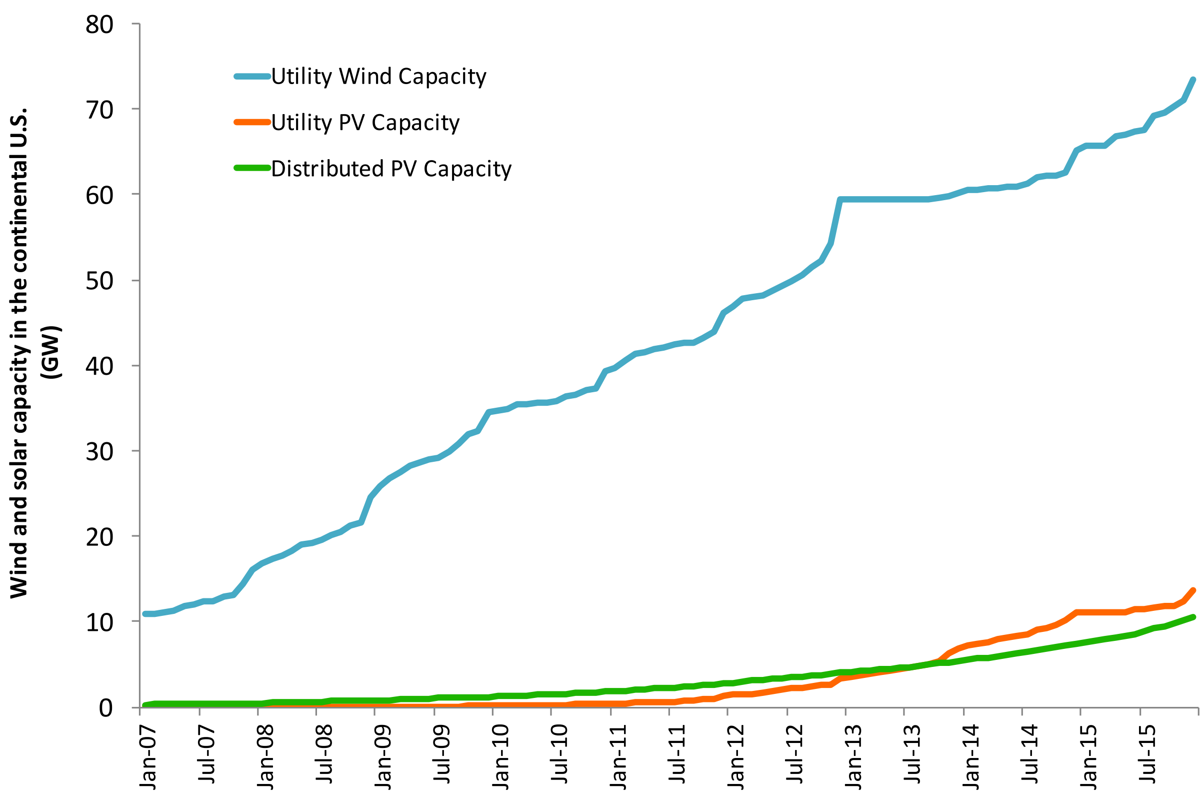
Wind and solar power can feasibly produce a large share of domestic generation and in doing so provide major air quality and climate benefits[1-4]. Previous studies have investigated renewable energy present-day benefits or benefits accrued over a limited historical time period at a national or multi-regional level[5-9] and have focused on single regions[10-12]. The scope and approach to representing both the impact of wind and solar generation on incumbent resources and to assessing the emission benefits and in some cases the monetary value of these benefits varies widely across these studies. However, to the best of our knowledge, no study has fully quantified U.S. wind and solar benefits over the past decade.

In this Analysis, we determine the magnitude and delivery location of all distributed solar, utility-scale solar and utility-scale wind generation across the continental United Sates from 2007 – 2015. We use a statistical model to find the SO_2, NO_x, $PM_{2.5}$, and CO_2 emissions that were likely avoided due to solar and wind generation. This set of emissions, tracked in related work[6,9,13-18], contributes to an important portion of total external-costs associated with electricity production[19]. We use a suite of reduced-form air quality models to estimate the public health benefits of reduced pollutant emissions. The range of estimates presented is driven both by uncertainty in the underlying processes and also by differences in model characteristics; note, our analysis does not represent a full assessment of underlying uncertainties. We also present a range of monetary climate benefits based on social cost of carbon (SCC) estimates spanning most of the range found in the literature. Finally, we investigate why benefits differ between regions and over time.

Solar and wind electricity generation

We developed a time series of wind and solar generation based primarily on Energy Information Administration[20] data. For solar generation, we relied on additional sources[21,22] (see Methods for details). The combined capacity of utility wind, utility solar, and distributed PV power sources increased from ~10 GW in 2007 to ~100 GW in 2015. Solar power capacity was negligible in 2007, but grew to ~25 GW (when combining utility and distributed capacity) by late 2015. Generation from these sources grew from 35,000 GWh/year in 2007 to 227,000 GWh/year in 2015. Solar power accounted for 17% of total wind and solar generation in 2015, up from <5% in 2007 (see Figure 1).

a



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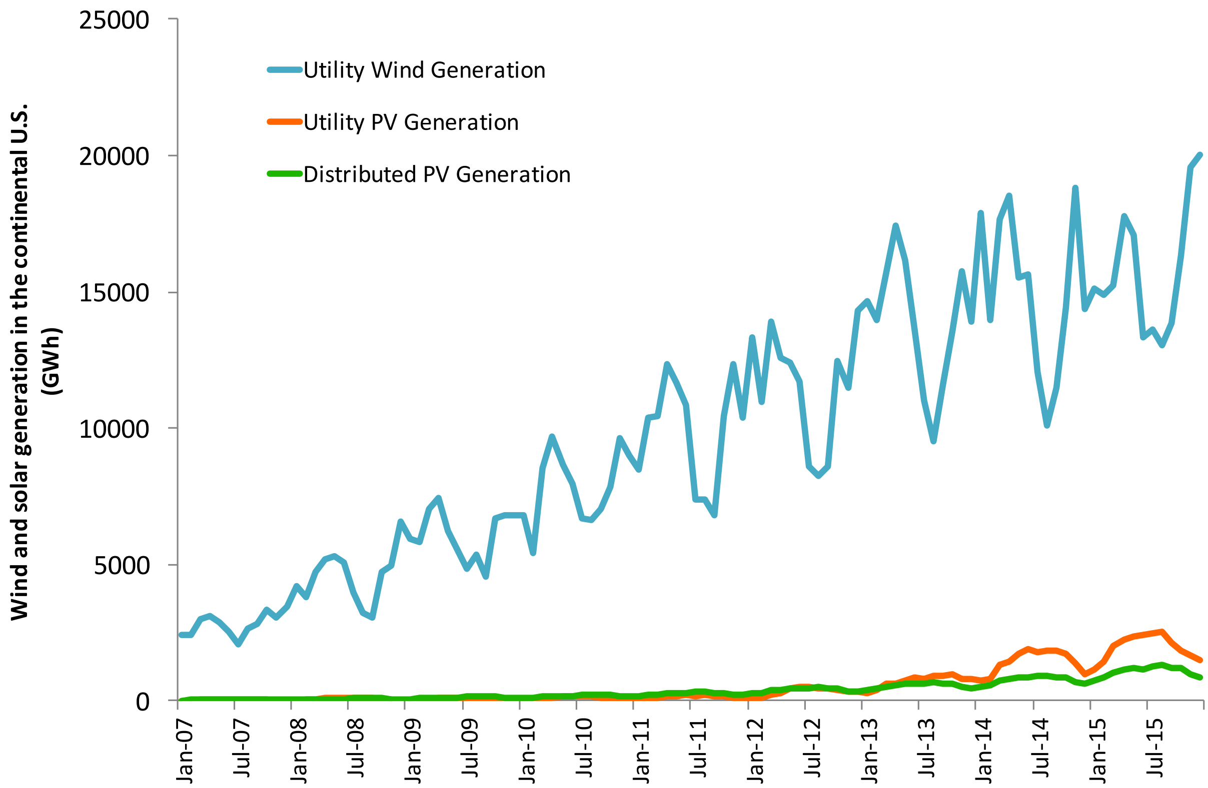


Figure 1. Total wind and solar capacity and generation in the continental U.S. by month. a, Capcity values. **b**, Generation values. Capacity and generation values are based on Energy Information Administration data[20] for wind and additional sources[21,22] for solar (see Methods).

These resources are not spread evenly across the continental U.S. (see Table 1). Most wind power has been deployed in the center of the country. In 2015, about 60% of wind power was delivered to the Upper and Lower Midwest and Texas regions and 10% and 12% of wind generation was delivered to California and mid-Atlantic regions, respectively (see Figure 2 for a map of these regions). Solar power is heavily concentrated in California, although less so in 2015 than in 2007. In 2007, 87% of total solar generation was delivered to California while in 2015 only 63% of solar power was delivered to California with 11%, 8%, 6%, and 6% of solar power delivered to the Southwest, Mid-Atlantic, Northeast and Southeast regions, respectively.

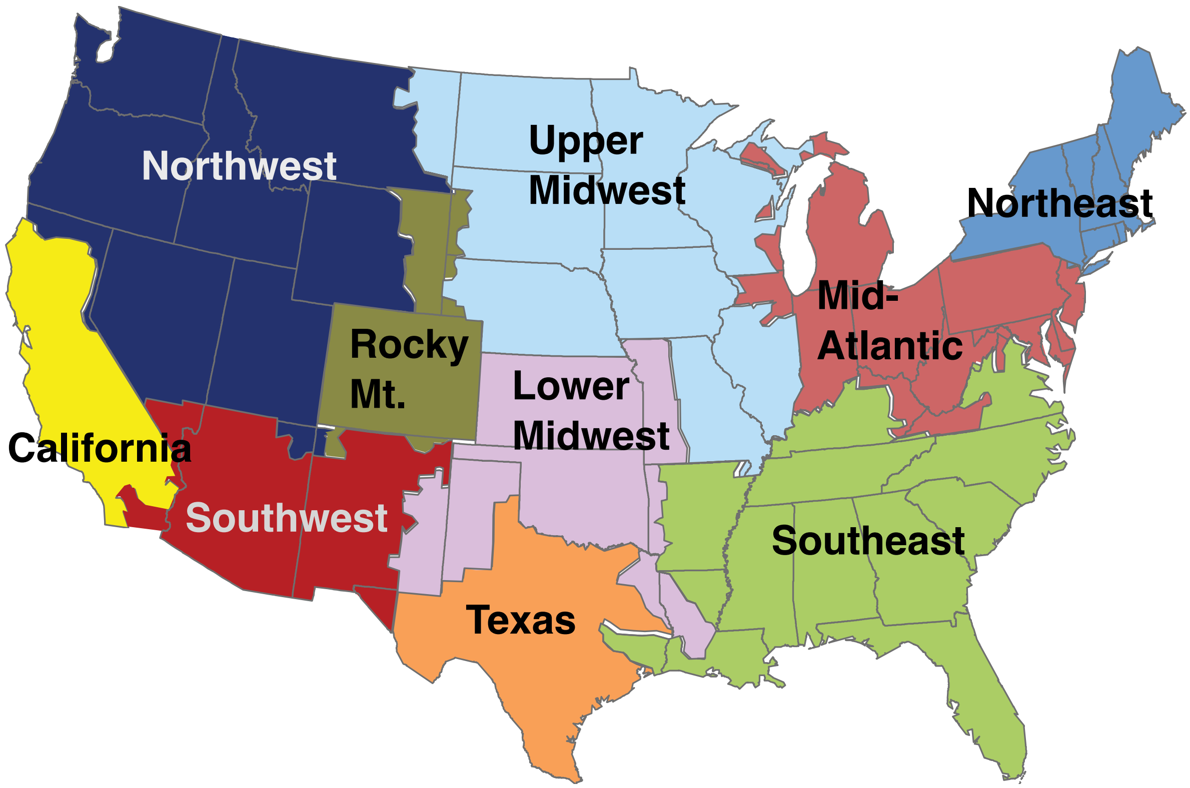


Figure 2. Regions within the AVERT model.

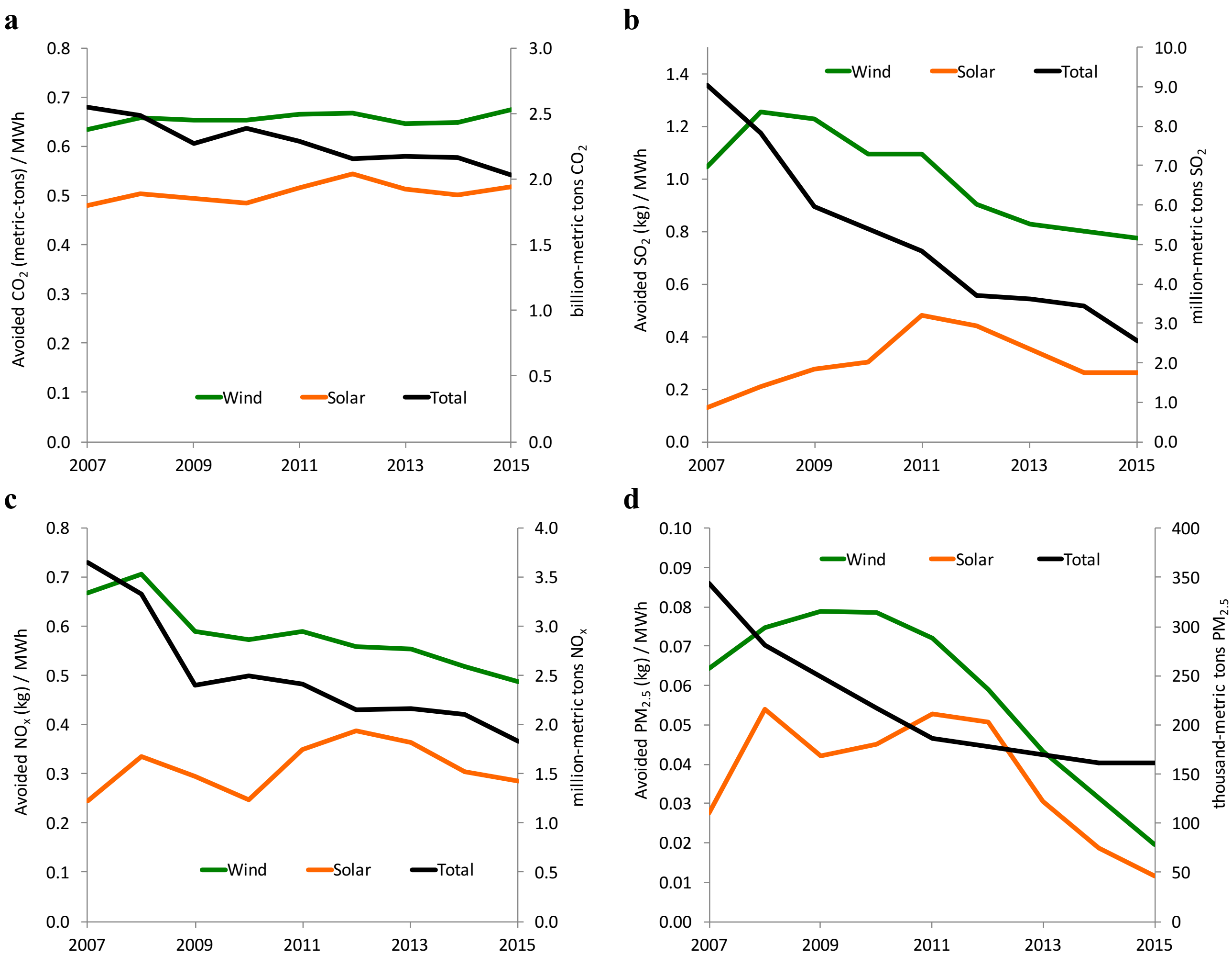
Table 1: Percentage of total generation. Generation values are based on Energy Information Administration data[20] for wind and additional sources[21,22] for solar (see Methods).

	Wind		Solar	
	2007	2015	2007	2015
Northwest	10%	7%	1%	1%
Rocky Mt.	6%	5%	1%	2%
Upper Midwest	20%	22%	0%	1%
Mid-Atlantic	4%	12%	3%	8%
Northeast	3%	3%	1%	6%
California	18%	10%	87%	63%
Southwest	1%	1%	7%	11%
Lower Midwest	15%	16%	0%	1%
Texas	24%	21%	0%	1%
Southeast	0%	3%	0%	6%

Avoided emissions

We estimated avoided generation and avoided emissions with the AVERT model[23]. We automated and then ran the model separately for solar and wind power and also for each region and year. Our analysis focuses on operational effects – which generators would have been utilized more without wind and solar generation. Not covered within this analysis is how wind and solar affect power plant new-build, retrofit, and retirement decisions. As wind and solar account for a greater portion of total generation, the impacts on long term investment decisions will require additional study. See Methods for details.

As shown in Fig. 3, between 2007 and 2015, total power sector emissions of CO_2, SO_2, NO_x, and $PM_{2.5}$ declined by 20%, 72%, 50%, and 46%, respectively. The most dramatic change in the power sector was to SO_2 emissions[24] which fell from 9.0 million metric tons in 2007 to 2.5 million metric tons in 2015 as coal power plants were fitted with new control technologies to meet air quality standards. However, wind's SO_2 and NO_x marginal emission benefits (metric-tons avoided per MWh generated) did not decline as quickly as overall power sector emissions, declining by only 26 and 27%, respectively. The marginal CO_2 emission benefits from wind increased. The marginal NO_x, SO_2, and CO_2 emission benefits from solar generation also increased over this time period.



e

f

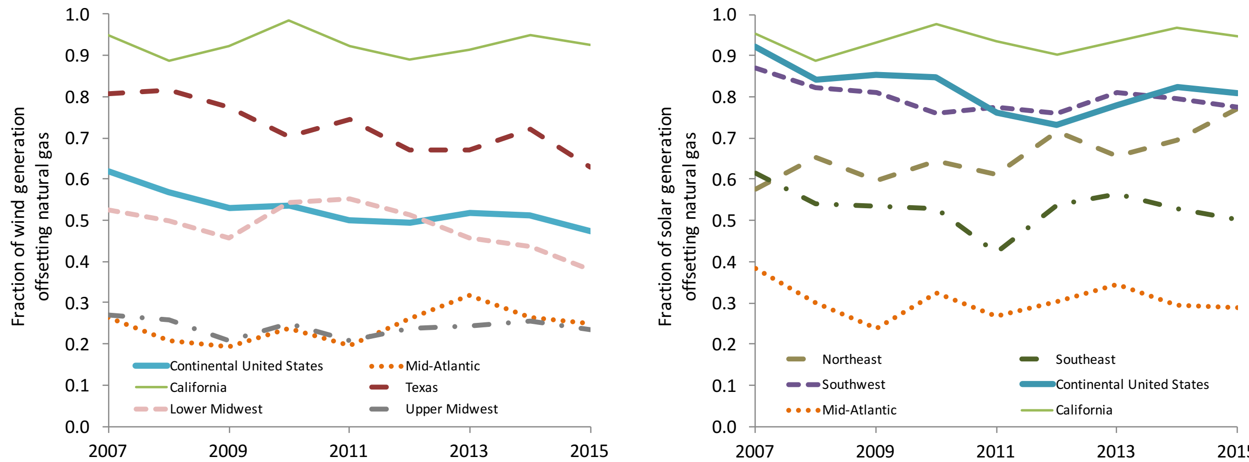


Figure 3 Marginal emissions benefits and proportion of generation offsetting natural gas. a – d, Marginal emission benefits (left axes) and total power sector emissions (right axes) of (a) CO_2, (b) SO_2, (c) NO_x, and (d) $PM_{2.5}$. Marginal emission benefits are calculated as the ratio of national avoided emissions (metric tons) to national generation (MWh-wind or MWh-solar). Total power sector emissions decline by more than the marginal emissions benefits. **e – f,** Fraction of (e) wind and (f) solar generation that offsets natural gas generation for the continental United States and selected regions. The regions selected represent the top five regions for each technology based on 2015 generation totals (see Table 1). Note that because other (non-gas and non-coal) generation types accounted for only a marginal amount of the total generation offset by wind and solar, with the exception of the New England region, the percentage of generation offsetting coal power can be approximated as the remaining percentage of generation after natural gas.

Our $PM_{2.5}$ emission reduction estimates are less certain than those for SO_2 and NO_x because, unlike SO_2 and NO_x, $PM_{2.5}$ is not continuously monitored at major power plant stacks. Our avoided $PM_{2.5}$ emissions estimates are derived from engineering based estimates[25,26] (see Methods). We estimate a steep reduction to marginal $PM_{2.5}$ emissions benefits between 2010 and 2015, but a similar reduction is not seen in the national emission inventory (see Figure 3). As we discuss below, $PM_{2.5}$ benefits are a small portion of the total benefits, thus we do not further refine the $PM_{2.5}$ emissions estimates.

Wind power growth outpaced declines in wind's marginal emission benefits leading to large growth in avoided emissions. Avoided emissions from solar also grew from increases in total generation and marginal benefits. Table 2 shows avoided emissions from solar and wind generation by pollutant and year and Supplementary Table 1 provides state and regional level details of avoided pollutants.

Table 2: Annual avoided emissions from wind and solar power.

	Wind (avoided metric tons)				Solar (avoided metric tons)			
Year	CO_2	SO_2	NO_x	$PM_{2.5}$	CO_2	SO_2	NO_x	$PM_{2.5}$
2007	21,459,000	35,000	23,000	2,000	850,000	200	400	50
2008	36,146,000	69,000	39,000	4,000	1,277,000	500	800	100
2009	47,681,000	90,000	43,000	6,000	1,519,000	800	900	100
2010	61,190,000	103,000	54,000	7,000	2,006,000	1,300	1,000	200
2011	79,052,000	130,000	70,000	9,000	3,007,000	2,800	2,000	300

2012	92,519,000	125,000	77,000	8,000	5,360,000	4,300	3,800	500
2013	107,582,000	138,000	92,000	7,000	8,470,000	5,800	6,000	500
2014	116,836,000	144,000	93,000	6,000	15,116,000	8,000	9,100	600
2015	127,698,000	147,000	92,000	4,000	19,392,000	9,900	10,700	400

Marginal emission benefits vary by region for three primary reasons. First, coal power generally has higher emissions rates of SO_2, NO_x, $PM_{2.5}$ and CO_2 compared to natural gas plants, thus regions with higher levels of coal power compared to natural gas power will see higher marginal emission benefits. Second, the emissions control technology on fossil fuel plants varies by both region and time. Third, the regional penetration level of renewable energy sources can influence which types of plants are avoided. This third category can vary over time with natural gas and coal fuel costs.

Between 2007 and 2015, wind power expanded into regions with the highest marginal benefits (the Upper Midwest and the Mid-Atlantic), particularly the highest SO_2 marginal benefits. In 2007, 24% of wind power was delivered to those regions but by 2015, that number had grown to 35%. At the same time, the relative amount of wind power delivered to California (the region with the lowest marginal emission benefits) fell from 18% to 10% (see Figure 3e,f and Table 1). Compared to California, the Upper Midwest and the Mid-Atlantic region relies more heavily on coal power and thus has larger marginal benefits.

Nationally, wind power offset more coal power in comparison to natural gas in 2015 compared to 2007. In 2007, 37% of wind generation offset coal generation and 62% offset natural gas generation. By 2015, 52% of wind power generation offset coal generation and 47% offset natural gas generation. Some of this shift can be attributed to the expansion of wind power into higher coal regions as described above, but we also saw a shift towards offsetting coal power over natural gas power within individual regions. For example, comparing 2007 to 2015, wind generation offset a slightly higher proportion of coal power in the Upper Midwest (73% to 77%) and Mid-Atlantic regions (70% to 73%) and wind generation offset a noticeably larger proportion in Texas (18% to 37%) and the Lower Midwest (48% to 62%), see Figure 3e,f and Table 1. These shifts—as estimated in AVERT—are coincident with, and likely partially result from, the drop in natural gas price that occurred between 2008 and 2012 as well as the increased penetration of wind supply.

Focusing on SO_2 emissions, wind power's average marginal emission benefit, for the subset of generation that offset coal generation, fell from 3.1 kg/MWh-coal to 1.6 kg/MWh-coal between 2007 and 2015. This decline, 48%, was not as large as the overall reduction to power sector SO_2 emissions, which on a marginal basis fell from 5.2 kg/MWh-coal to 1.9 kg/MWh-coal. Thus, the emission rate from coal plants that responded to wind power was 41% lower than average coal plants in 2007, but only 15% lower by 2015.

To summarize, there are three reasons why the decline to wind power marginal emission benefits was slower than the decline to overall power sector emissions: first, wind expanded into relatively high emitting regions; second, within many regions, a higher proportion of wind power offset coal power in 2015 than in 2007; and third, wind power offset a cleaner-than-average set of generators in 2007 and that distinction was diminished by 2015. The story for solar power includes the same trends as wind power, however, regional change (the expansion out of

California) to solar power dominates. Solar power expanded into the Northeast, Mid-Atlantic, and Southeast regions by 2015. These regions combined accounted for 20% of solar generation in 2015 up from only 4% in 2007.

Avoided damages

To address the uncertainty related to air pollution, we apply a suite of air quality models as outlined in the Methods. Each of these models covers slightly different impact pathways. We estimate the monetary and physical benefits and report the range and a simple average of these model results. The range across the models primarily reflects variation in the treatment of the transport and atmospheric transformation (e.g. sulfur dioxide gas to sulfate particulate matter) of emitted pollutants. Some of the models contain a high and low benefit estimate based on two different epidemiological estimates of the population response to exposure to particulate matter. The range of values presented simply represents the range of the current state-of-the-science estimates of the air pollution impacts and does not represent a true confidence interval. Additional discussion of these topics is presented in the Methods. Finally, most of the monetary value reported here derives from the application of the value of statistical life (VSL) to the avoided incidences of premature mortality; however, some additional value is derived from reduced morbidity estimates incorporated in a subset of the models.

To address uncertainty related to the valuation of GHG emissions we base our results on a wide range of SCC values. The SCC is an estimate, including both positive and negative effects, of the net present monetary value of a 1 metric-ton increase in CO_2 emissions. The climate impacts covered by SCC estimates typically include changes to agricultural productivity, energy use, loses from disasters such as floods, human health and general ecosystem services[27]. We include a low (7.0 \$/metric-ton), central (37 \$/metric-ton), and high value (125 \$/metric-ton) to roughly bracket the range of values in the literature; see the Methods section for further discussion. While air pollution benefits represent benefits accrued within the borders of the United States, the GHG benefits represent global economic benefits.

Table 3: Cumulative and 2015 benefits from avoided air pollution and avoided GHG emissions. Total benefits and average marginal benefits are calculated across all regions for the time period indicated. Average marginal benefits are calculated as the ratio of national benefits (¢) to national generation (kWh-wind or kWh-solar). The range of air pollution benefits reflects the range across the suite of air quality models and the range of GHG benefits reflects the range across the SCC estimates.

	2007 – 2015				2015			
	Total Benefits		Avg. Marginal Benefits (¢/kWh)		Total Benefits		Avg. Marginal Benefits (¢/kWh)	
	Central	Range	Central	Range	Central	Range	Central	Range
Monetary benefits (billions 2015\$US)								
Wind air pollution	54.0	28.4 – 107.9	5.1	2.7 – 10.3	8.1	4.3 – 15.9	4.3	2.3 – 8.4
Solar air pollution	2.3	1.3 – 4.9	2.1	1.1 – 4.4	0.7	0.4 – 1.4	1.7	0.9 – 3.6

Wind GHG	29.0		4.9 – 98.5		2.8	0.5 – 9.4	5.7		1.0 – 19.3		3.0	0.5 – 10.2
Solar GHG	2.5		0.4 – 8.3		2.2	0.4 – 7.5	0.9		0.1 – 2.9		2.3	0.4 – 7.8
Avoided mortalities												
Wind air pollution		6,700		2,900 – 12,200				1,000		400 – 1,700		
Solar air pollution		300		100 – 500				80		40 – 150		

Emissions avoided due to wind generation between 2007 and 2015 produced \$28.4–\$107.9 billion (central value of \$54.0 billion, equivalent to 5.1 ¢/kWh) in air quality and public health benefits and \$4.9–98.5 billion (central value of \$29.0 billion, equivalent to 2.8 ¢/kWh) in climate benefits. Additional details can be seen in Table 3 and Supplementary Tables 2– 4.

During the study period wind generation led to the avoidance of 2,900 – 12,200 premature mortalities, with solar generation contributing another 100 – 500 to those totals. See additional details in Table 3. Depending on the model, avoided SO_2 emissions accounted for 74% – 87% and 64% – 76% of the wind and solar power benefits, respectively, and avoided NO_x emissions accounted for 8% – 15% and 12% – 21% of the wind and solar power benefits, respectively. The exception to this was in the Penn et al.[28] model: avoided SO_2 accounted for 45% and 37% of wind and solar benefits, respectively, and avoided NO_x accounted for 35% and 47% of wind and solar benefits, respectively. Avoided $PM_{2.5}$ emissions contributed a small portion of the total benefits across all the models.

The growth in wind power climate benefits was relatively consistent over the time period while the growth in air quality benefits largely plateaued between 2011 and 2015 (see Figure 4). This plateau was due primarily to the power sector SO_2 emission reductions. The continued growth of climate benefits, between 2011 and 2015, occurred as wind power deployment outpaced power sector CO_2 emissions reductions.

Between 2007 and 2015 emissions avoided due to solar generation produced \$1.3–\$4.9 billion (central value of \$2.3 billion, equivalent to 2.1 ¢/kWh) in air quality and public health benefits and \$0.4–\$8.3 billion (central value of \$2.5 billion, equivalent to 2.2 ¢/kWh) in climate benefits. See Table 3 for additional details. The growth in solar power outpaced the decline in overall power sector emissions of air pollutants and GHG, and both air quality and climate benefits grew strongly through 2015.

a **b**

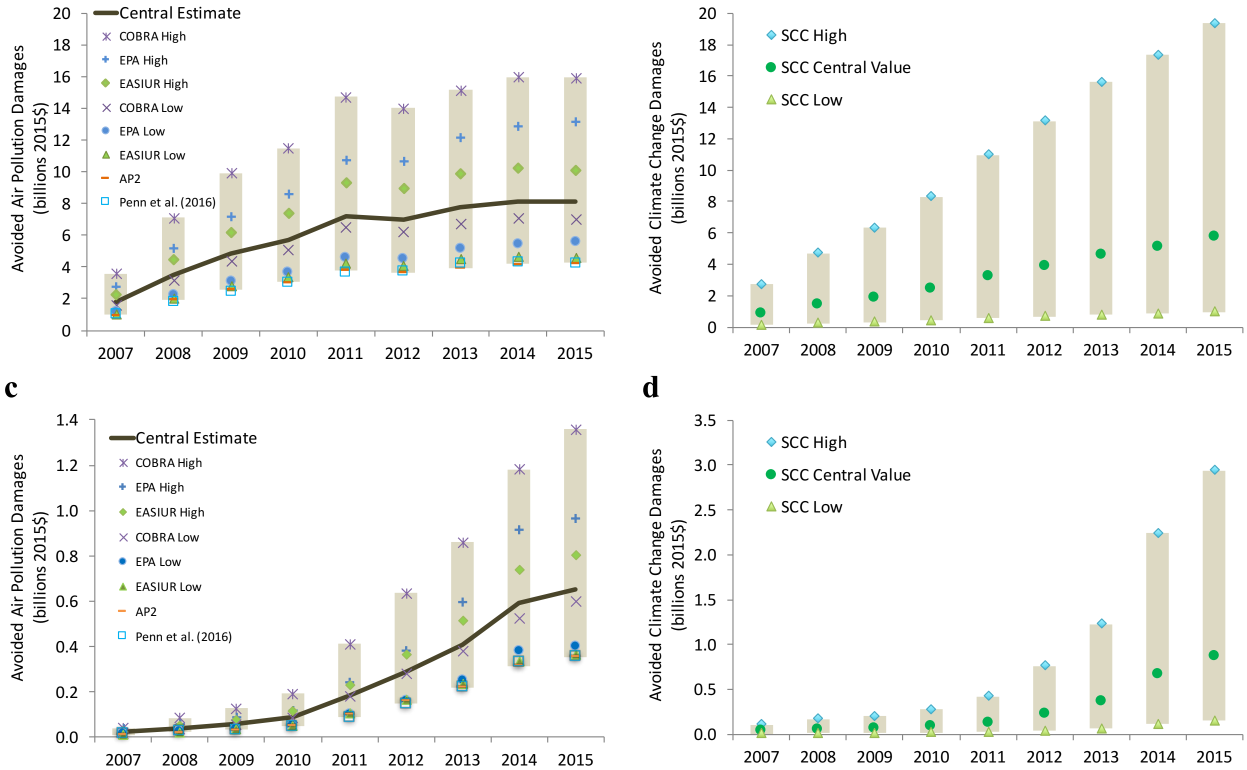


Figure 4: Annual avoided air quality and climate damages. a, annual air pollution benefits from wind power. **b**, annual climate benefits from wind power. **c**, annual air pollution benefits from solar power. **d**, annual climate benefits from solar power. The bars represent the range of benefits spanning the range of air quality models (**a** and **c**) or the SCC estimates (**b** and **d**).

There are important regional variations to these benefits, see Figure 5. For example, in 2015, California saw the smallest marginal wind benefits, 0.4 ¢/kWh and 2.1 ¢/kWh in air quality and climate benefits, respectively. The Mid-Atlantic region saw the largest air quality and climate wind benefits of 11.0 ¢/kWh and 3.3 ¢/kWh, respectively. These regions also show the largest differences between air quality and climate benefits, with the marginal climate benefits worth five times the air quality benefits in California, but air quality benefits worth roughly four times the climate benefits in the Mid-Atlantic. The difference between air quality and climate benefits is primarily driven by regional differences to air quality benefits, as climate benefits have relatively small regional variation. As discussed above, the regional differences in air quality benefits are strongly dependent on the type of generation being offset; however, other factors also contribute to differences across regions, especially variations in the proximity and size of population impacted by power sector emissions. For example, on a per ton basis, one of the air quality models (the EPA RIA model, see Methods) values SO_2 emission reductions in the Eastern U.S. at approximately five times those in the western U.S., and similar regional variation is found in the other air quality models. Thus, per ton emission benefits from the mid-Atlantic region, which has large emitters in close proximity to large population centers, are more highly valued than those from the western U.S. coal plants, which are not located in close proximity to population centers. Finally, though this discussion of regional variation is based on central estimates, we note the context of the large range of benefits estimates shown in Figure 4.

The breakdown of the regional trends highlights the impacts of recent power sector pollution controls. For example, Figure 5a,b shows a dramatic drop in the marginal air quality benefits from both wind and solar across the Upper Midwest and along the Atlantic coast. However, Figure 5c,d indicates that in most regions the growth of wind and solar outpaced the decline in marginal benefits.

Compared with the variation in marginal benefits between regions, the variation in marginal benefits between wind and solar is small. Within each region, the marginal air quality and climate benefits of wind and solar power are generally similar. For example, in 2015, the largest difference in air quality marginal benefit between the two technologies was in the Southwest where benefits from wind power, at 1.0 ¢/kWh, were 21% larger than those of solar power. In 2015, the largest difference between wind and solar marginal climate benefits was only 2% (in the North-West region). There were somewhat larger differences between the technologies prior to 2015, likely because of the larger price variations between natural gas and coal in earlier years that leads to greater time-varying marginal emissions rates.

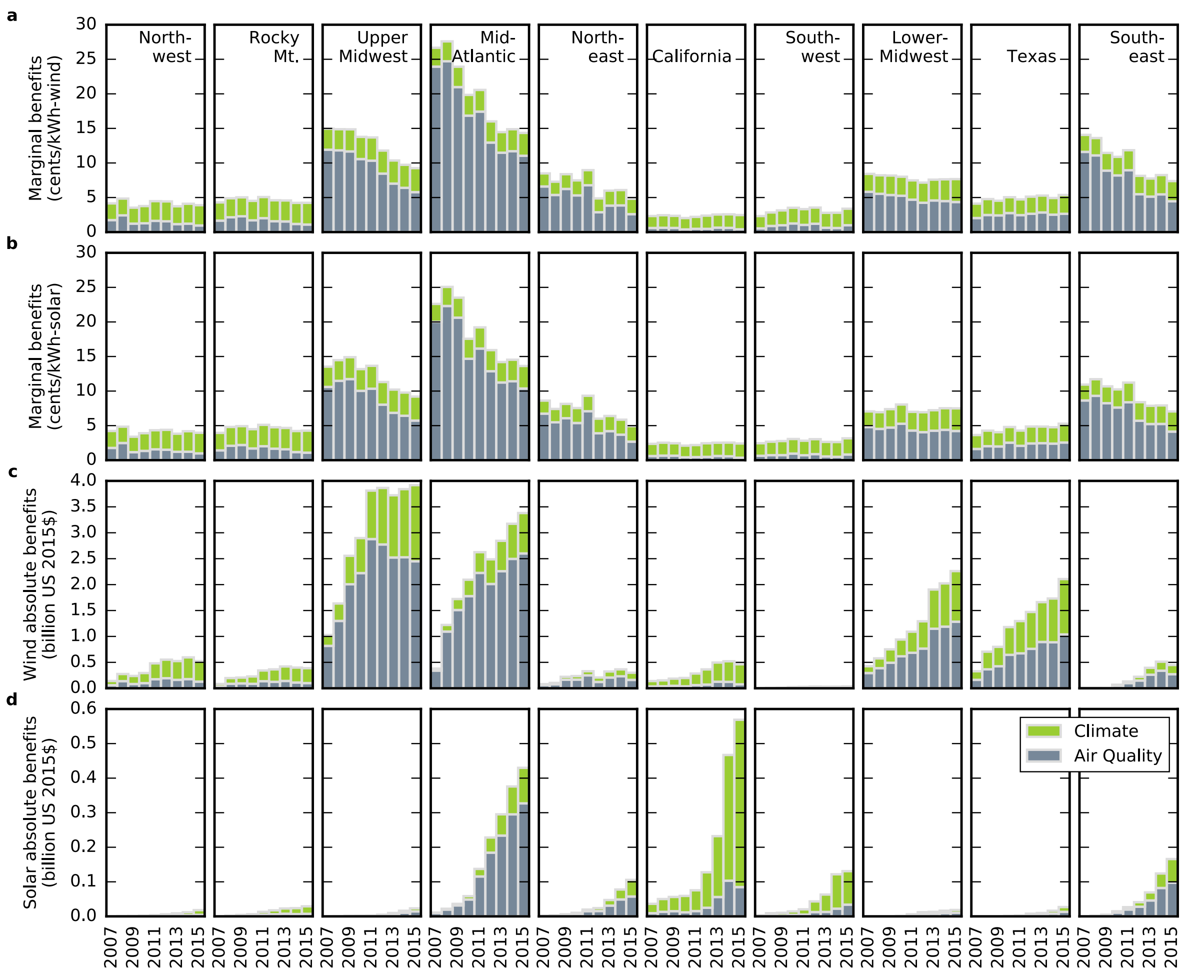


Figure 5: Annual benefits by region. . **a**, Marginal benefits (¢/kWh) from wind power. **b**, Marginal benefits from solar power. **c**, Absolute benefits (billion US 2015$) from wind power. **d**, Absolute benefits from solar power. In all panels, the gray and green bars represent air quality and climate benefits, respectively.

Comparison to incentives and market prices

Overall, our results are consistent with prior work including refs [9,29]. However, we find larger benefits relative to Siler-Evans et al.[9] due to our use of updated air quality impact models. We find benefits similar in magnitude to Buonocore et al.[29], although their detailed focus on the Mid-Atlantic region shows larger variation in the marginal benefits between wind and solar.

The central value national air pollution and climate benefits in 2015 are estimated at 7.3 ¢/kWh (wind) and 4.0 ¢/kWh (solar), but there is significant variation over time and geography, and a wide range of estimates given underlying uncertainties. To put these estimates in context, one can compare them to current levelized cost of energy estimates (LCOE), the price of wind and solar energy, and to federal and state incentives for those resources.

As shown in Supplementary Note 1, these benefits are on par with, or greater in many cases, than recent direct prices paid for wind and solar, and also recent estimates of the LCOE of wind and utility solar (the LCOE of residential rooftop solar remains higher).

The United States has a long history of offering direct incentives for energy development, technologies, and use. Wind has recently received the production tax credit (2.3 ¢/kWh, for 10-years) and solar a 30% investment tax credit. Wind and solar also receive other forms of federal and state tax and financial support, including through accelerated tax depreciation and R&D spending and state level policies. Though the purpose of these federal and state incentives is not solely to obtain near-term air quality and environmental benefits, total central-value wind and solar air quality and climate benefits calculated earlier--$8.7 billion in 2010, $13.6 billion in 2013, $15.9 billion in 2015--are comparable to estimates of total federal and state financial support (see Supplementary Note 1).

Given these comparison values, it is clear that the air quality and climate change benefits from wind and solar power are relatively large. That being said, those benefits vary significantly by region, whereas most incentives for wind and solar do not similarly vary by region as a means of directing deployment to those areas with the greatest benefits. Where incentives do differ regionally or by technology—e.g., due to state-level support—those variations are not, in general, related to the locational dependence of air quality and environmental benefits. Related, and in part as a consequence, addressing air quality and climate change through policies directly supporting wind and solar is not necessarily the most cost-effective approach[30-35]. The decline in the marginal emission benefits discussed earlier, for example, indicates the success of a number of alternate strategies to directly address power-sector air pollution impacts. However, simply because a *theoretical* cheaper path to address these impacts may exist does not mean we should discount the benefits already accrued and currently accruing from non-emitting generating sources. Additionally, the uncertainty surrounding future power sector air quality and GHG emission regulations provides motivation to assess the value of wind and solar.

Impact of cap-and-trade programs

Under a strictly binding cap and trade system for air pollution, the value of emission displacement would change as wind and solar would cause a shift in timing of emissions but would not reduce the overall annual emission totals, as those are set by the cap. Under this scenario, Siler-Evans et al.[9] argue the marginal monetary benefit of displaced emission could be valued at the allowance prices to reflect the cost of complying with the annual emission cap, while the health impact value would be set at zero to reflect that annual emissions remain constant. The most relevant trading programs to this work are the SO_2 and NO_x trading within the Clean Air Interstate Rule (CAIR) and the Cross-State Air Pollution Rule (CSAPR) as well as the GHG trading within the Regional Greenhouse Gas Initiative (RGGI) in the Northeast and the California Cap and Trade Program. If these programs maintained effective binding caps it would negate the air quality or climate benefits calculated here. However, if emissions were unrestrained by these programs, with annual emissions falling consistently below the caps, then we assume displaced emissions were truly avoided and not simply shifted to another hour and location during the same year.

Within Supplementary Note 2, we present evidence that large-scale cap and trade programs did not generally produce binding caps during this time period. Thus, we do not develop alternate valuations of wind and solar power based on allowance prices. However, it is possible that wind and solar power produced some shifting in timing, rather than reductions, of emissions under CAIR during 2009 and 2010. The air quality benefits calculated for CAIR regions in 2009-2010 account for up to 16% of the cumulative national air quality benefits over the full-time period. The impacts of a binding NO_x cap should be kept in mind if special focus is paid to the benefits found within CAIR states during those years. Although we do not find evidence for a binding carbon cap in California and RGGI, benefits from California, accrued after the start of the trading program, and from the Northeast region from 2014 – 2015, representing the period after RGGI reduced its cap, accounted for a small portion of overall benefits: 4% of the combined air quality and climate change benefits and 8% of the climate change benefits alone. Notwithstanding these findings of limited impacts to date of binding cap and trade, wind and solar emission benefits could potentially be limited in future years if cap and trade programs become binding.

Conclusions

Over the last decade, the wind and solar industry experienced high growth while major changes to the power sector substantially reduced emissions of criteria pollutants and carbon dioxide. Given that the air quality and climate benefits of wind and solar power have been cited as reasons for public support, we sought to understand how these benefits have changed over time, and what they are sensitive too.

One important finding is that while marginal emission benefits from wind and solar have decreased, they have not decreased at the same rate as emissions from the overall power sector. There are three reasons for this: both wind and solar expanded into regions with higher marginal benefits; wind and solar offset more coal power relative to natural gas power at the end of the time period; and the mix of incumbent coal generators that likely curtailed generation in response to wind and solar power was relatively cleaner at the beginning of the time period. This relatively slow decline to marginal wind and solar benefits combined with rapid growth in wind and solar generation results in growing annual air quality and climate benefits within the time period analyzed.

We compared the magnitude of the air quality and climate monetary benefits of wind and solar to both recent wind and solar power sales prices and to estimates of federal and state financial support. Our central value, national average estimates for these benefits was of similar magnitude to both comparison values. However, consistent with past work, we find large differences between regional marginal air quality benefits, owing to both lower marginal emission benefits and lower per ton valuation of emission benefits for regions in the west compared with those in the east. Interestingly, we find relatively small differences when comparing wind and solar within regions: cross-region differences far outweigh differences caused by the varying temporal output profiles of wind and solar plants. Compared to air quality benefits, marginal emission benefits for CO_2 were relatively consistent across the country. In order to represent underlying uncertainty, we used a range of SCC estimates to value avoided GHG emissions and a suite of air quality models to value avoided air pollution. On a national average basis, and using central estimates, the combined air quality and climate benefits provide some justification for current levels of public and private support of these technologies. However, refined policy mechanisms that either directly target unpriced externalities or alternatively that direct wind and solar deployment to those regions of the country that offer the greatest benefits (at the least cost) would offer additional gain.

Methods

Estimating Air Emissions Impacts. We use EPA's Avoided Emissions and geneRation Tool (AVERT) model to estimate the historical impacts of wind and solar generation on U.S. air emissions. The AVERT model was developed to determine which electricity generators would be most likely to respond to either the addition or removal of non-dispatchable resources such as wind or solar power, or energy efficiency measures. In other words, the AVERT model finds the generators on the margin at each hour of the year and returns those generators along with their emission characteristics, allowing us to calculate the emissions impact of removing the existing wind and solar resources from the power sector. This approach produces a more detailed estimate of emission displacement than could be done from using simple regional average emission rates while allowing us to provide continental coverage over a nine-year period. It also allows us to investigate changes over time to the mix of generators on the margin. AVERT does not, however, allow us to directly account for cap-and-trade regulations or to capture changes to investment decisions in fossil plants that might vary depending on the level of renewable energy deployment. AVERT also has limited representation of interactions across regions and provides no information about within-region variations. AVERT does not include explicit ramping or cycling impacts, however, previous studies suggest these impacts are relatively small (e.g. Lew et al.[36]). Further details can be found in refs[23,37,38]. Additionally, see refs[5,28,39,40] for examples of AVERT being applied to answer similar questions as are asked in this paper.

In the present study, we automated AVERTv1.4 to generate 180 model runs capturing generation and emissions displaced by wind and solar across 10 regions and nine years. The AVERT model is based on the historical generation patterns of each individual year and thus annual generation inputs were prepared separately for each year. The earliest year available within the AVERT model is 2007, and thus our analysis runs from 2007 – 2015, capturing roughly an order of magnitude in growth in both wind and solar generation. AVERT produces estimates of avoided SO_2 and NO_x emissions, but does not produce estimates of avoided direct emissions of $PM_{2.5}$. We estimate $PM_{2.5}$ emissions as a function of avoided generation by plant type (coal, gas or oil) and state-level emission rates reported in refs[25,26]. These works estimate plant level emission factors by combining plant level heat input data and plant level emission control system characteristics with literature-based $PM_{2.5}$ emission factors (mass per unit fuel use), and then report average state-level emission rates by plant type. All state-level $PM_{2.5}$ emissions were reduced by a national scaler to represent the reduction in $PM_{2.5}$ emission factors described between 2010 and 2015 by Cai et al.[26].

To use the AVERT model we need to develop hourly profiles of historical generation from wind and solar power. We also need to account for where the electricity was delivered (to one of 10 AVERT regions across the continental U.S., see Figure 2) as opposed to relying on the physical power plant location. For example, a number of wind and solar projects export their electricity to other states and regions. We do not need to account for value transfers, such as Renewable Energy Certificates (RECs), as we are only interested in determining which power plants were on the margin and would have been utilized had the solar or wind resource not been available during a specific hour, a determination dependent on the delivery location of the electricity. We split this task into parts by finding a separate time series by industry segment: utility wind, utility solar, and distributed solar.

Utility Wind Power Generation. Monthly generation records (in MWh) for all individual utility wind power plants are recorded by the U.S. Energy Information Administration (EIA)[41]. These records are available for the entire time period of interest. We then assigned each wind plant, ~930 active anytime between 2007 – 2015, to one of 10 AVERT regions based on the location to where it delivered electricity. To determine the AVERT delivery region we first determined the U.S. state of the wind project using EIA 860 data[20]. We then determined, using the American Wind Energy Association (AWEA) wind project data base[42], AWEA transfer data[43], Federal Energy Regulatory Commission *Electric Quarterly Reports*[44], and the Wind Technology Market Report[45] whether the wind project delivered electricity to a local utility or other local entity or exported it to a non-local entity. If the electricity was delivered locally, and the State was completely contained within one AVERT region, we assigned that region to the wind project. If the electricity was delivered locally, but the State contained two or more AVERT regions, we assigned the wind project to one of the possible AVERT regions based on matching the county of the wind project and/or the map of the local entity to the map of the AVERT regions. Finally, if the electricity was exported to an entity outside the region or state of the wind project we assigned the wind project to the AVERT region that matched with location of the entity to which the electricity was exported. We did not include exports that were based on financial contracts such as Renewable Energy Credits, and counted only exports that required cross-region delivery; we acknowledge that even when cross-region delivery is required, there may not be an exact match between renewable energy production and cross-regional electricity flow. Exports of wind power across AVERT regions accounted for 1.8% of total wind generation in 2007 and 7.2% of the total in 2015. We tracked a limited number of wind projects which began exporting their electricity to a new location midway through the analysis period, however, the vast majority of wind projects maintained the same delivery location throughout. To convert the monthly wind power generation to hourly generation we applied the regional hourly profiles for wind power, available within AVERT, as hourly weights to each month's recorded generation. We developed the hourly generation based on the region in which each wind project was based and, for plants that exported energy to a different region, transferred this hourly generation to that destination region.

Utility Solar Power Generation. Similar to the utility wind power generation, the U.S. EIA records all generation from utility solar power plants, including both solar thermal and solar photovoltaic. The EIA keeps records only for plants larger than 1 MW in capacity. We followed a similar methodology as was used for utility wind plants to determine the AVERT region into which each plant, ~1270 total, delivered electricity. In this case, we again depended on data from EIA forms 860 and 923 as well as the FERC EQR data[44], but also used the Utility Scale Solar Report[46] data base, to determine the delivery location for each solar plant. For utility PV, out of region transfers accounted for 11.6% of the total generation in 2015, up from negligible transfers in 2007 and 2008, and mostly from transfers into California from neighboring states. We again used AVERT regional hourly profiles, this time based on the utility solar profiles, to divide regional monthly generation into hourly generation. We used a custom hourly profile for solar thermal power including storage technology, however, this applied to only two plants during the time period.

Distributed Solar Power Generation. This category includes all solar power plants that are too small (< 1 MW) to be counted within EIA's utility solar database. This includes not only commercial type installations but also rooftop residential solar installations. EIA has begun to provide an estimate of distributed solar power generation, but the estimate only goes back to the beginning of 2014. Unlike the utility generation, distributed generators are often consumer owned and/or located behind the electricity meter, making it challenging or impossible to record generation statistics from all installations. Generation estimates must therefore be made based on installed capacity. The EIA distributed solar estimates are made in this manner, combining distributed capacity by state with the PVWatts model[47,48]. We follow a similar approach to develop distributed solar generation estimates back to 2007.

First we develop an estimate of total distributed solar power capacity back to 2007. Our primary source for this estimate is the annual reports developed by GTM Research[21]. These reports contain solar power capacity by quarter and U.S. State. The GTM reports divide solar capacity into three categories, utility, non-residential, and residential. These categories do not match up exactly with the EIA categories. To reconcile the two data sets and avoid double counting capacity, we find total distributed capacity by subtracting the EIA utility solar capacity (EIA 860) from the total solar capacity from all three GTM categories. In general, the EIA utility capacity accounted for all of the GTM utility category plus some of the GTM non-residential category.

There are a number of details to account for within this process. First, the GTM data was only available from 2010 – 2015, so, prior to 2010 we used data collected by the Interstate Renewable Energy Council[22] to account for deployed capacity by state on an annual basis. Additionally, GTM data includes state level data for 34 states, with the remaining 1.2% of the total GTM capacity assigned to an 'other' category. We distributed this other category across the remaining states based on the relative PV capacity of these states as determined in the IREC data set. We used the simplifying assumption that new capacity was deployed equally across the three months of each quarter, or across each year 2007 – 2009. We also had to synchronize EIA and GTM capacity deployment in time, as there were a few instances when EIA listed a utility project start date one quarter earlier or later compared to the GTM record.

Finally, to develop hourly distributed PV production estimates we applied the hourly AVERT profiles to the monthly capacity estimates. The AVERT profiles were developed based on using the PVWatts model, in a similar manner to method used by EIA described above. To determine the allocation of state-level distributed PV capacity to AVERT region, we developed AVERT region weights for each state based on the number of utility customers within each AVERT region within each state. EIA provides a list of all utilities and their number of customers and MW served which we used to assign each utility to an AVERT region based on the location of its service area. Note that, unlike the utility-scale categories, we assumed no transfers across regions for the distributed solar category.

Our estimate largely agrees with EIA's distributed solar estimate. Our 2014 and 2015 total distributed solar generation equaled 86 and 97% of EIA's total, respectively.

Valuation of Air Quality Benefits. To estimate the value of reductions to pollutants SO_2, NO_x and $PM_{2.5}$ we use a suite of models: EASIUR[49,50], the impact factor model developed in Penn et al.[28] and Levy et al.[39], Air Pollution Emission Experiments and Policy analysis model (AP2, formerly APEEP: Muller et al.[51,52]), EPA RIA[53] benefits per ton estimates, and COBRA[54]. Each of these models captures somewhat different impact pathways, as described further below. Moreover, the methodology underlying these reduced-order models varies based on the treatment of the transport and transformation of pollutants between the time of emission and human exposure. Additionally, each of these models with the exception of AP2 and Penn et al.[28], includes an estimate of the benefits based on two different representations[55,56] of the underlying epidemiological relationships related to the additional risk of mortality from increased exposure to $PM_{2.5}$. Penn et al.[28] report central estimate impacts factors based on Roman et al.[57], rather than a high and low estimate. A similar central estimate technique has been used in other studies, such as Driscoll et al.[58] One subtlety to note regarding $PM_{2.5}$ exposure: In the *Estimating Air Emissions Impacts* section above we described estimates of avoided direct emissions of $PM_{2.5}$, however, the avoided health damages described in this section are largely driven by avoided exposure to *all* types of $PM_{2.5}$ including particulate sulfate and nitrate. Particulate sulfate and nitrate form in the atmosphere, as a consequence of SO_x and NO_x gaseous emissions, but are directly emitted by power plants in relatively small quantities.

We report a central estimate based on a simple average of the set of models and we also report the range across the models. This approach allows us to treat each model as equally valid, meaning our results are not especially dependent on a single model. However, the methods and approaches across the models do differ in their level of sophistication. The EASIUR, Penn et al., and EPA RIA models are all based on state-of-the art, full fate and transport air quality models, while COBRA and AP2 are based on a simpler air quality dispersion modeling technique. EASIUR contains more finely resolved spatial resolution compared to the EPA and Penn et al. models, and is also based on a longer modeling timespan than the Penn et al. model. In that sense, EASIUR is the best suited of the models for our purpose. We note that the values produced by EASIUR are within 10% of our central estimate values.

The EASIUR model[49,50] produces an estimate of the monetary value of the reduced emissions of $PM_{2.5}$ and $PM_{2.5}$ precursors (such as NO_x and SO_2) derived solely from the reduced risk of premature mortality from reduced annual exposure to $PM_{2.5}$. We used EASUIR estimates of the marginal damage per metric ton of NO_x, SO_2, and $PM_{2.5}$ emission at stack-level height by U.S. county. The reduced-order EASIUR model depends on a regional-scale chemical transport model, the Comprehensive Air Quality Model with extensions (CAMx)[59], which was run with a module that 'tagged' emissions from particular locations and tracked each location's emissions contribution to average $PM_{2.5}$ levels. EPA used a similar general approach for its RIA analysis. However, the EPA developed regional benefit per ton estimates for three large regions across the continental U.S. Additionally, the EPA included estimates of not only mortality benefits from reduced $PM_{2.5}$ exposure, but instead mortality and morbidity benefits from reduced $PM_{2.5}$ and ozone exposure. EPA states that greater than 90% of the per ton total monetary benefits are due to reduced mortality rates[53].

Penn et al.[28] also depends on a regional-scale chemical transport model, CMAQ[60,61]. CMAQ was run with the decoupled direct method, which allowed the model to isolate the sensitivity of pollutant concentration levels to precursor emission rates. The sensitivity levels were used to generate the state-level impact factors reported in Penn et al.[28], which we used in our avoided damage calculations. Like EASIUR, Penn et al.[28] impact factors also derive solely from reduced risk of premature mortality from reduced annual exposure to $PM_{2.5}$ and were developed specifically for estimating the impacts of emissions originating from power plants.

The COBRA and AP2 models represent a different approach to modeling the air quality chemistry and transport. These models employee the Climatological Regional Dispersion Model (CRDM)[62], which uses a Gaussian dispersion model to represent atmospheric transport. While this technique has some limitations, see the introductory discussion in Heo et al.[50], it does provide an independent modeling methodology from the CAMx based modeling used in EASIUR and EPA RIA. We used COBRA and AP2 estimates of the benefits per ton of reduced emissions of SO_2, NO_x, and $PM_{2.5}$. The COBRA and AP2 models both include monetary estimates of the impacts of mortality and morbidity impacts from $PM_{2.5}$ exposure. The AP2 model also includes ozone exposure impacts as well some additional monetary benefits from other environmental impacts, such as reduced crop yields and reduced visibility. However, most of the monetary value in these models derives from reduced premature mortality. The AP2 model provides marginal impacts at the county level which we applied to avoided emission at the county level. The COBRA model was automated and run separately for each state and pollutant allowing us to calculate impacts based on state level avoided emissions.

The EPA RIA, COBRA, and Penn et al.[28] models allow us to derive not only per ton monetary value but also per ton morbidity and mortality incidences. We report total avoided instances of premature mortality based on output from this subset of models.

Valuation of GHG Emission Reductions. The social cost of carbon (SCC) is an estimate of the present value of the societal cost of releasing an additional metric-ton of carbon. As there is wide uncertainty about the social costs of climate change, there is also a wide range of SCC estimates. For our purpose, we aim to report the valuation of GHG emissions reductions based on a range of SCC values that is consistent with the current literature.

Refs[63-65] summarize SCC estimates through meta-analyses. Tol's most recent work[65] includes an analysis of 75 studies, finding mean and median values of $53/tCO2 and $37/tCO2, respectively, with a standard deviation across the studies equal to $88/tCO2. Nordhaus[66] provides one of the most recent, and updated, estimates of the SCC. While this estimate is not based on a meta-analysis of many studies, it does produce a range of SCC values based on an analysis of structural uncertainty (i.e., the influence of parametrizations within their model such as productivity growth, equilibrium temperature sensitivity, and damage functions). This uncertainty analysis follows the approach developed by Gillingham et al.[67]. Nordhaus[66] finds that the 10^{th} to 90^{th} percentile range of the SCC is $7/tCO2 to $77/tCO2, with a central estimate of $32/tCO2.

There are many criticisms of the approaches used to develop the SCC (see the discussion in Nordhaus[68] and Ackerman et al.[69]). Some argue that the meta-analyses median and mean values are biased low as the underlying studies ignore many impact pathways (e.g. large biodiversity losses and political instability), do not adequately account for extreme and irreversible climate change, and are often based on relatively high social discount rates[70,71]. Given those considerations, van den Bergh and Botzen[70] suggest that, if one applies a precautionary approach when valuing the risk of extreme climate change, a conservative, *lower bound* SCC value of 125 $/tCO2 is justified.

To produce the range reported in our paper, we use the median value, 37 $/tCO2, from ref. [65] as our central value. This central value is similar to the central value in Nordhaus[66]. For our lower bound, we use $7/tCO2, the 10th percentile estimate from Nordhaus[66]. This value is approximately the 30th percentile of the distribution of estimates summarized by Tol[65], and is also on the low end of other ranges in the literature, such as suggested by Havranek et al[72]. We set the high end of our range to 125 $/tCO2 based on van den Bergh and Botzen[70]. We note that this high-end estimate roughly brackets the meta-analysis from Tol[65] with 125 $/tCO2 equaling approximately the 85th percentile of all estimates summarized therein.

The above estimates from Tol[65] represent the 2010 SCC. For simplicity, we treat our high estimate (of 125 $/tCO2) as a 2010 SCC value as well. Tol[65] finds the median growth rate of the SCC estimates to be 2.2% across the studies included in the meta-analysis. We apply this growth rate to our central and high range estimates to develop SCC values for each year between 2007 and 2015. The Nordhaus[66] values represent the SCC for 2015 and we adjust the value backwards using the stated growth rate of 3%. We also adjust all the estimates to dollar year 2015.

Data availability.
All source data from the US EIA and FERC is publically available at no charge. EIA forms 860 (generator capacity) and 923 (monthly generation) can be found at https://www.eia.gov/electricity/data/detail-data.html. FERC electronic quarterly reports can be downloaded from https://eqrreportviewer.ferc.gov/. Supplementary Tables 1-4 contain detailed annual data from our results, including state-level avoided emissions and regional monetary and mortality benefits. Additional data that support the findings of this study are available from the corresponding author upon reasonable request.

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Author contributions
All authors jointly developed the research design. D.M. carried out all the simulations and analyzed the model outcomes. With input from all authors, D.M. led the overall manuscript development. R.W. provided critical input and review throughout the manuscript. M.B. and R.W. led development of the comparison to incentives and market prices. G.B., D.M. and R.W. developed the distributed solar generation estimates.